

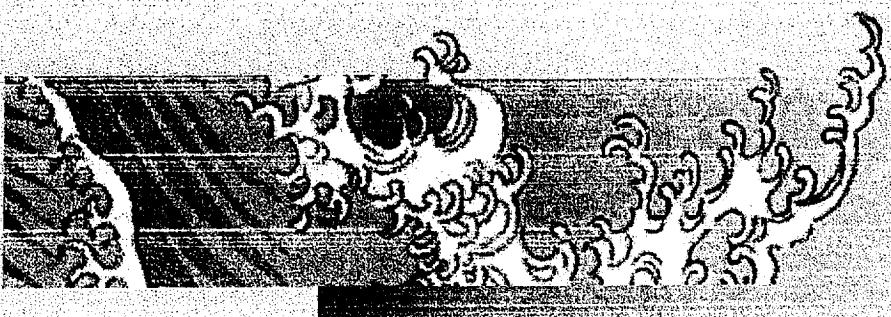
# **Efficient High Order Central Schemes for Multi-Dimensional Hamilton-Jacobi Equations**

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# **Outline**

- ★ Introduction
- ★ 1st and 2nd order methods
- ★ High-order methods
- ★ Conclusions



# Hamilton-Jacobi Equations

- ★ Equations of the form  $\varphi_t + H(\varphi_x) = 0$
- ★ Where we assume  $H$  is at least continuous
- ★ Evolves discontinuous derivatives even from smooth initial data
- ★ Viscosity Solution (Crandall, Lions, Evans)
- ★ Applications in control theory, optics, ...
- ★ Encounter high-dimensional spaces



# Numerical Methods for HJ

- ★ Numerical Methods for HJ Eqns
- ★ Complicated by non-smoothness of solutions
- ★ Known to converge to viscosity solution (Souganitis)
- ★ Adapt techniques from conservation laws
  - ★ Flux limiters, WENO, Central methods
- ★ Our Goal: *high-order, efficient, central methods that scale well to high dimension*



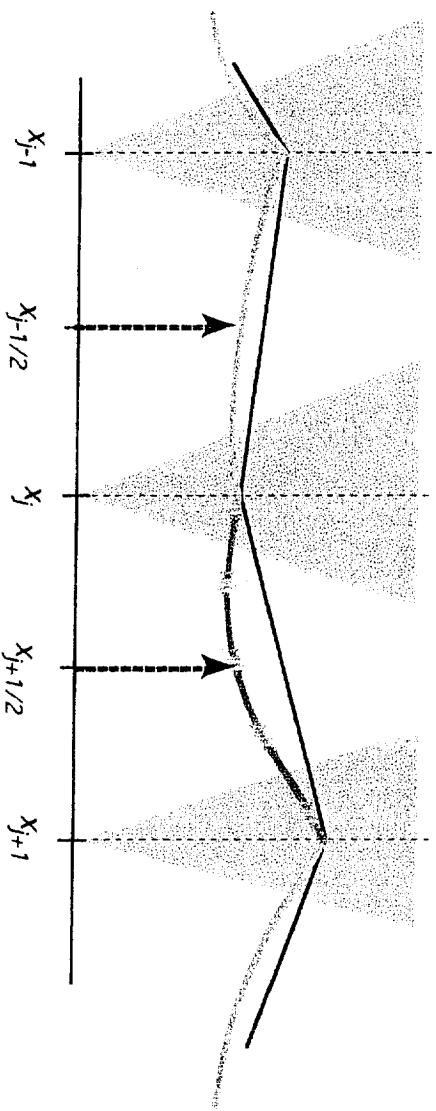
# Existing Work

- ★ Upwind Schemes
  - ★ Osher and Shu - high-order ENO methods
  - ★ Jiang and Peng - high-order WENO methods
- ★ Central Schemes
  - ★ Lin and Tadmor - 1st and 2nd order staggered
  - ★ Minmod flux limiter on 1st derivative
  - ★ Proved 1st order convergence
- ★ Kurganov and Tadmor - 1st and 2nd order semi-discrete
  - ★ Minmod limiter on 2nd derivative
  - ★ reduce dissipation by estimating local speed of propagation

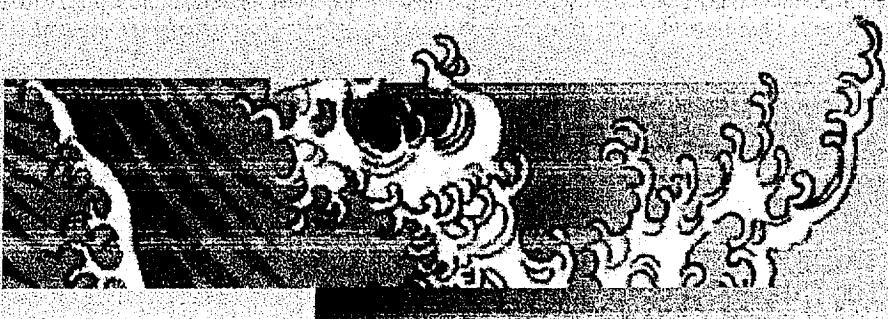


# The Central Philosophy

- ★ Evolve where data is smooth

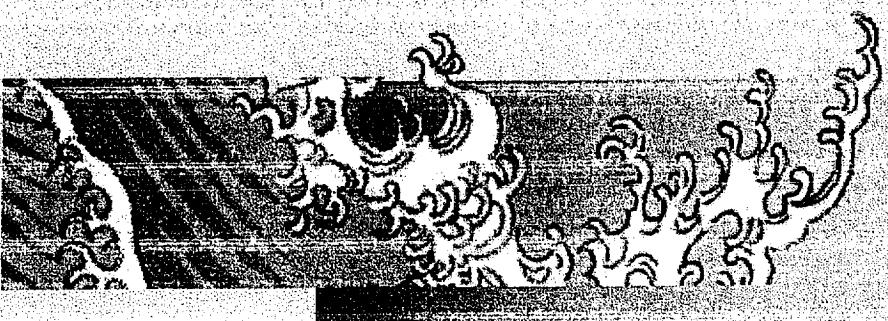


- ★ Steps: *reconstruct, evolve, reproject*
- ★ Avoid solving Riemann problems
- ★ Good for systems and high dimensions



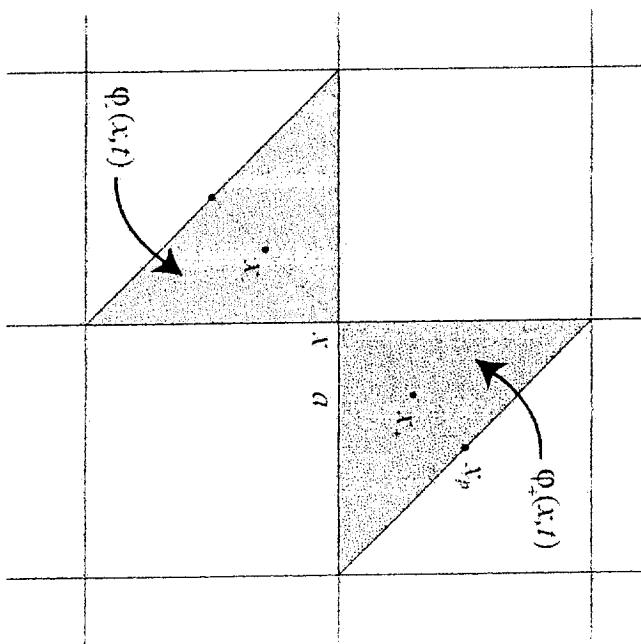
# First and Second Order

- ★ Limit the second derivatives and reproject onto original grid points
- ★ Based on Lin-Tadmor and Kurganov-Tadmor
- ★ Same work as Lin-Tadmor in 2D
- ★ Evolve at evolution points using quadrature
  - ★ 1st-order method:
- ★ 
$$\varphi^{n+1} = \varphi^n + \frac{1}{4} \left( (\Delta\varphi)_{i+\frac{1}{2}}^n - (\Delta\varphi)_{i-\frac{1}{2}}^n \right) - \frac{\Delta t}{2} \left[ H \left( \frac{(\Delta\varphi)_{i+\frac{1}{2}}^n}{\Delta x} \right) + H \left( \frac{(\Delta\varphi)_{i-\frac{1}{2}}^n}{\Delta x} \right) \right]$$
- ★ Use Taylor expansion for mid-values in 2nd-order midpoint quadrature
- ★ Assumes  $H \in C^1$



# Evolution in $R^n$

- ★ Partition space into simplices along + and - diagonal
- ★ Singularities along simplex boundaries
- ★ Optimal Evolution Points
- ★ Equidistant from simplex boundaries



$$\alpha = \frac{1}{n + \sqrt{n}}$$

# 2nd-Order Generalization to $\mathbb{R}^n$

▲ Reconstruct via polynomial

$$\varphi_z(x, t^m) = \varphi_\alpha + \sum_{k=1}^n \frac{\Delta_k^\pm \varphi_\alpha^m}{\Delta x} (x^{(k)} - x_\alpha^{(k)}) + \frac{1}{2} \sum_{k=1}^n \frac{\mathcal{D}_k \Delta_k^\pm \varphi_\alpha^m}{(\Delta x)^2} (x^{(k)} - x_{\alpha \pm \epsilon_k}^{(k)}) + \frac{1}{2} \sum_{j=1, j \neq k}^n \sum_{l=j}^n \frac{\mathcal{D}_j \Delta_k^\pm \varphi_\alpha^m}{(\Delta x)^2} (x^{(j)} - x_\alpha^{(j)}) (x^{(k)} - x_\alpha^{(k)})$$

▲ Where  $\mathcal{D}$  is the min-mod limited derivative

At evolution points: at each point  $x_\alpha$

$$\varphi_\pm^m = \varphi_\alpha^m + \alpha \sum_{k=1}^n \Delta_k^\pm \varphi_\alpha^m + \frac{\alpha(\alpha-1)}{2} \sum_{k=1}^n \mathcal{D}_k \Delta_k^\pm \varphi_\alpha^m + \frac{\alpha^2}{2} \sum_{j=1}^n \sum_{k=1}^n \mathcal{D}_j \Delta_k^\pm \varphi_\alpha^m$$

$$\left( \frac{\partial \varphi}{\partial x^{(p)}} \right)_\pm^m = \frac{\Delta_p^\pm \varphi_\alpha^m}{\Delta x} \pm \frac{2\alpha-1}{2} \frac{\mathcal{D}_p \Delta_p^\pm \varphi_\alpha^m}{\Delta x} \pm \frac{\alpha^2}{2} \sum_{k=1}^{k=p} \frac{\mathcal{D}_p \Delta_k^\pm \varphi_\alpha^m + \mathcal{D}_k \Delta_p^\pm \varphi_\alpha^m}{\Delta x}$$

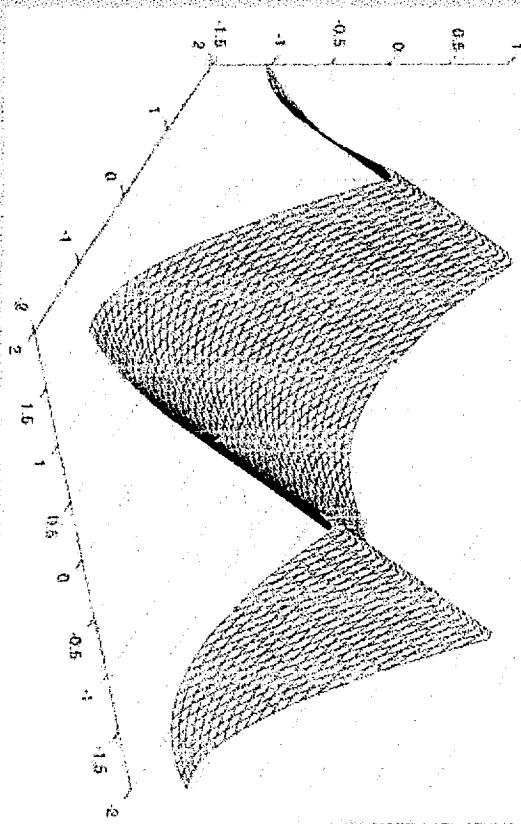
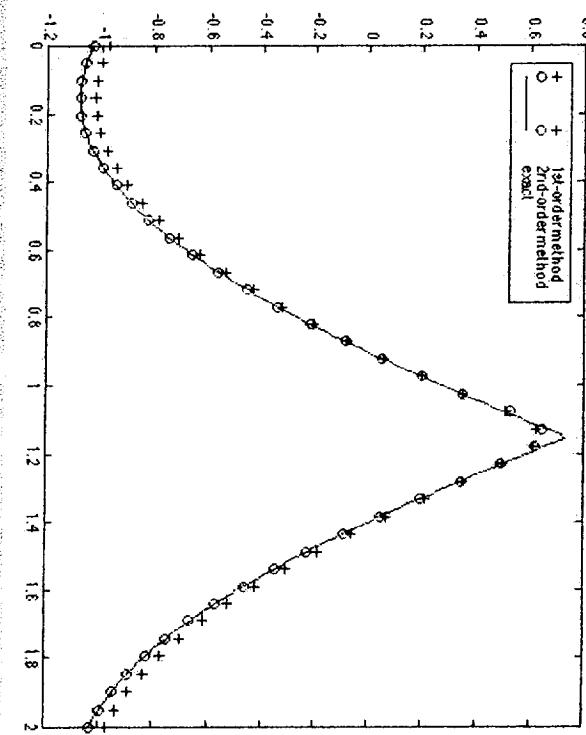
$$\left( \frac{\partial \varphi}{\partial x^{(p)}} \right)_\pm^{m+\frac{1}{2}} = \left( \frac{\partial \varphi}{\partial x^{(p)}} \right)_\pm^m - \frac{\Delta t}{2} \left[ H_p \left( (\nabla \varphi)_\pm^m \right) + \sum_{k=1}^n H_{\varphi_p} \left( (\nabla \varphi)_\pm^m \right) \frac{\mathcal{D}_p \Delta_k^\pm \varphi_\alpha^m + \mathcal{D}_k \Delta_p^\pm \varphi_\alpha^m}{2(\Delta x)^2} \right]$$

$$\varphi_\pm^{m+1} = \varphi_\pm^m - \Delta t H \left( (\nabla \varphi)_\pm^{m+\frac{1}{2}} \right) \quad \text{where} \quad (\nabla \varphi)_\pm^m = \left( \left( \frac{\partial \varphi}{\partial x^{(1)}} \right)_\pm^m, \dots, \left( \frac{\partial \varphi}{\partial x^{(n)}} \right)_\pm^m \right)$$

▲ Reproject:  $\varphi_\alpha^{m+1} = \frac{1}{2} (\varphi_+^m + \varphi_-^m) - \alpha^2 \sqrt{n} \Delta x \mathcal{D}(d\varphi)_0^{m+1}$

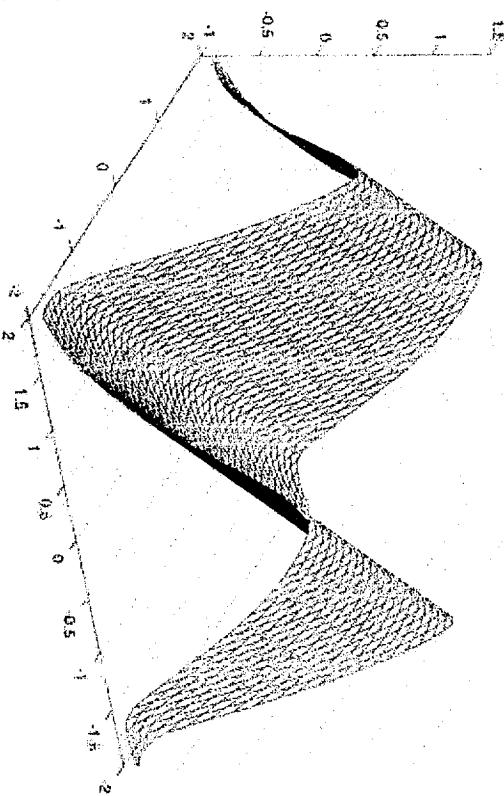
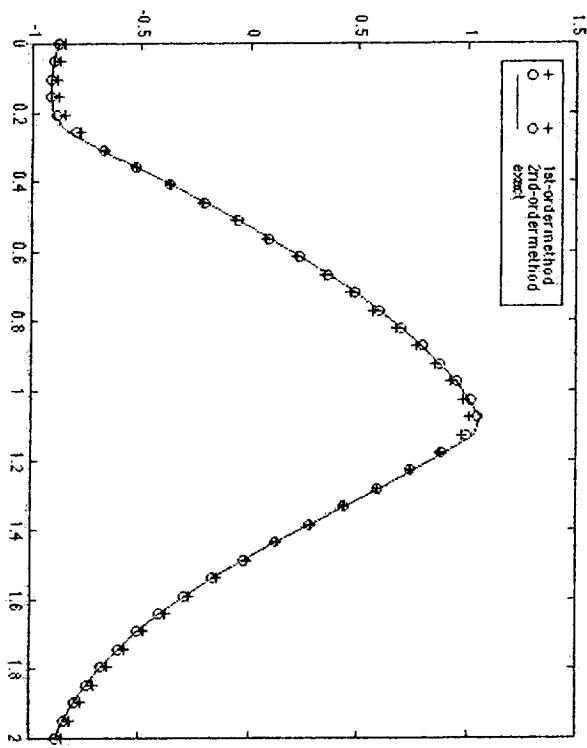
# Convex H Example

$$\begin{cases} \varphi_t + \frac{1}{2}(\varphi_x + 1)^2 = 0 \\ \varphi_t + \frac{1}{2}(\varphi_x + \varphi_y + 1)^2 = 0 \\ \varphi(x, 0) = -\cos(\frac{1}{2}\pi(x + y)) \end{cases}$$



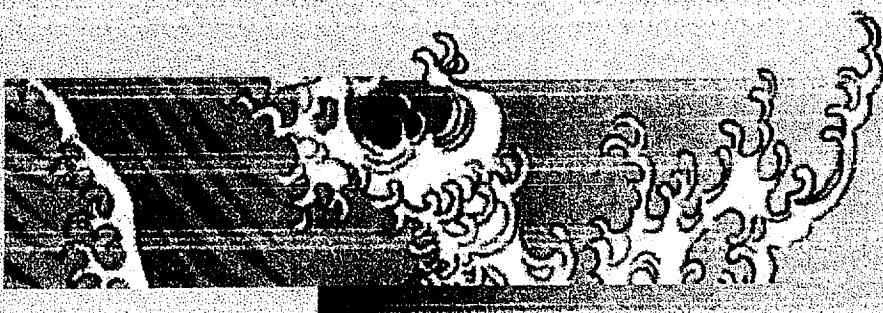
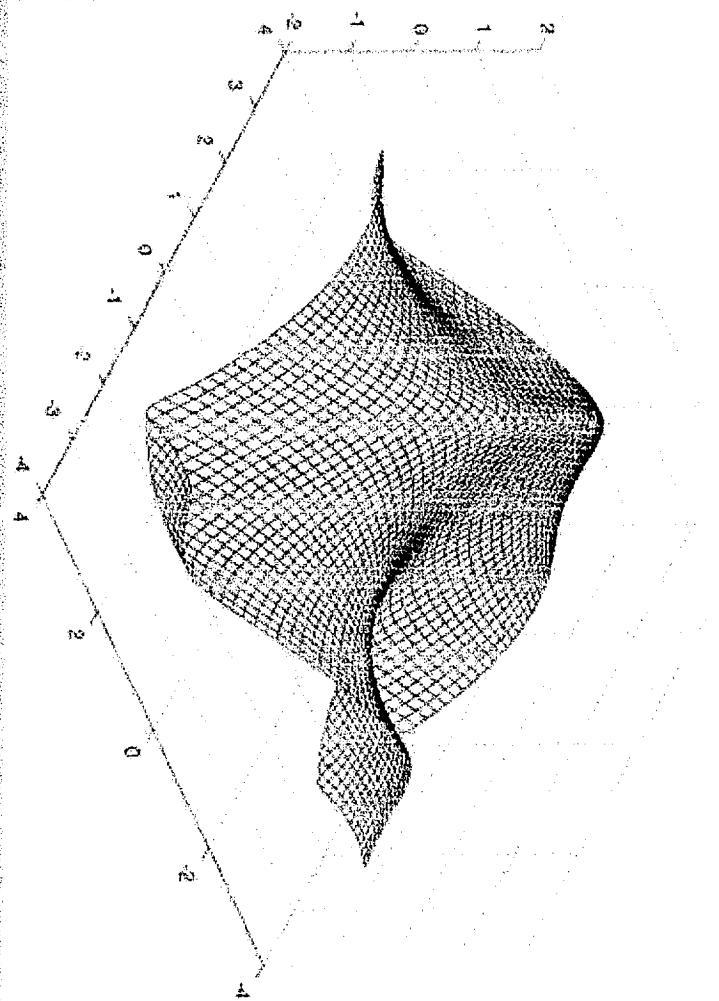
# Non-Convex H Example

$$\begin{cases} \varphi_t - \cos(\varphi_x + 1) = 0 \\ \varphi_t - \cos(\varphi_x + \varphi_y + 1) = 0 \end{cases}, \quad \begin{cases} \varphi(x, 0) = -\cos(\pi x), \\ \varphi(x, y, 0) = -\cos\left(\frac{1}{2}\pi(x + y)\right) \end{cases}$$

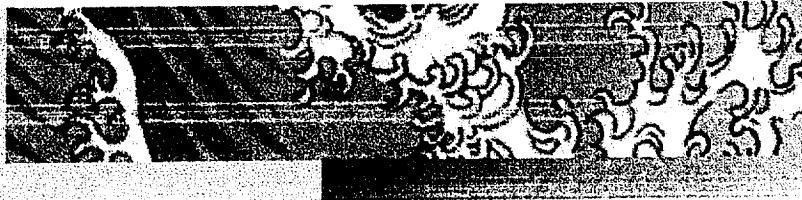
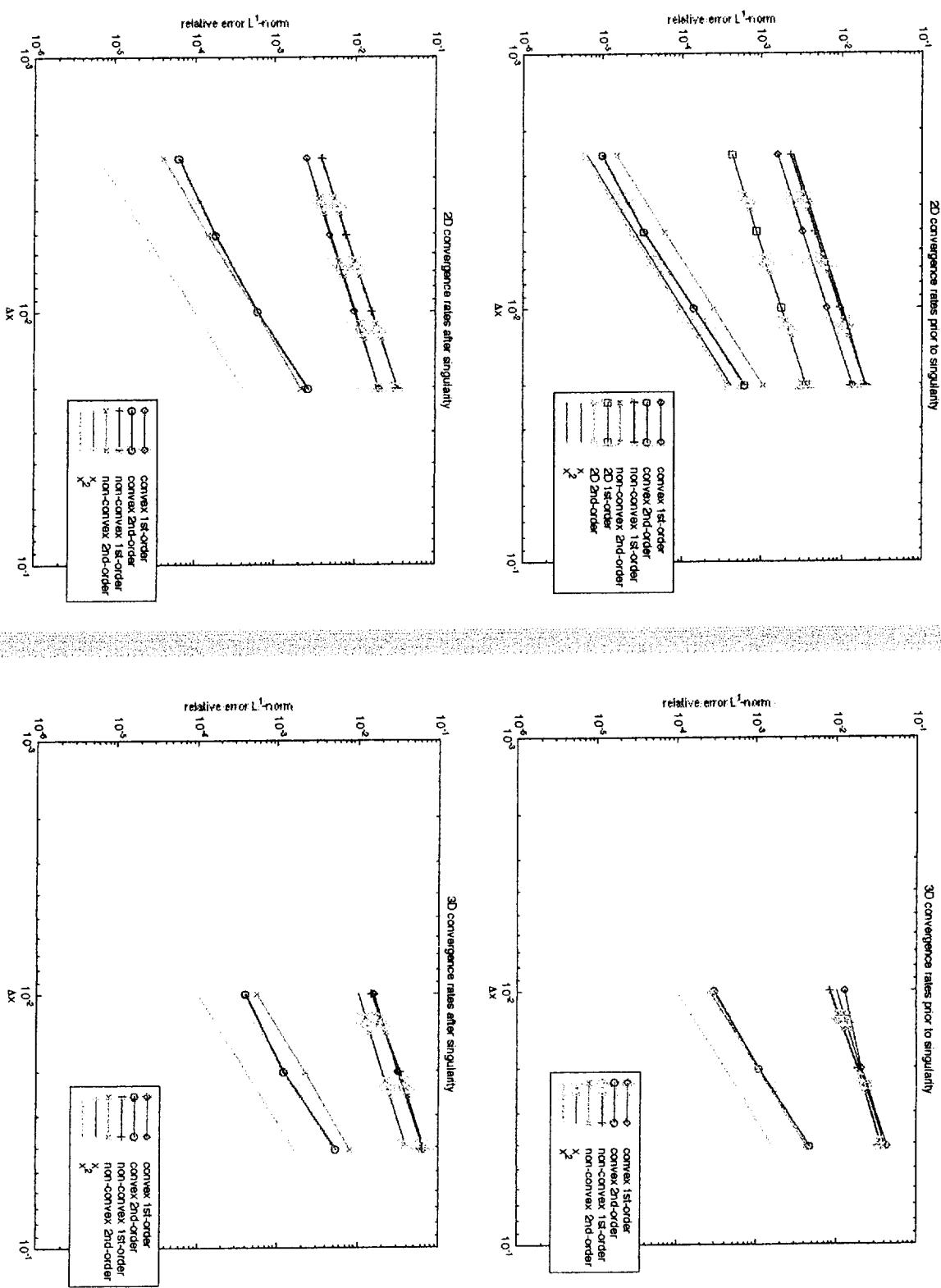


## 2D Example

$$\left\{ \begin{array}{l} \phi_t + \phi_x \phi_y = 0 \\ \phi(x, y, 0) = \sin(x) + \cos(y) \end{array} \right.$$

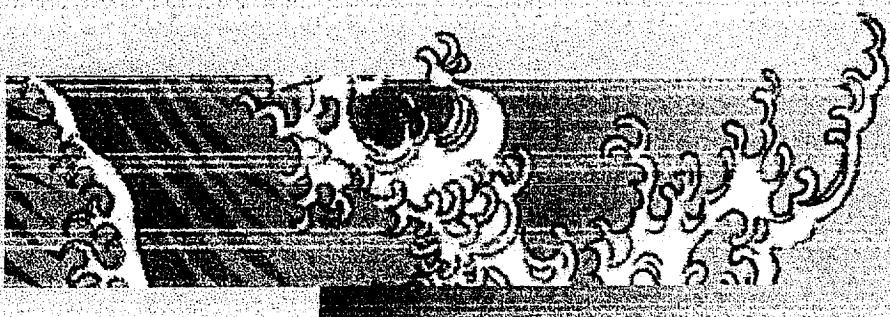


# Convergence Rates



# Higher Order

- ★ Strategy:
- ★ Central WENO for reconstructions
- ★ Simpson's formula/SSP RK4 for evolution
- ★ Involves upwind WENO reconstruction of derivatives for each RK4 step



# High-order 1D Interpolants

## 3rd-order example

$$\varphi_1(x_i + a\Delta x) = \left( -\frac{1}{2}a + \frac{1}{2}a^2 \right) \varphi_{i-1} + (1-a^2)\varphi_i + \left( \frac{1}{2}a + \frac{1}{2}a^2 \right) \varphi_{i+1} = \varphi(x_i + ah) + O((\Delta x)^3)$$

$$\varphi_2(x_i + a\Delta x) = \left( 1 - \frac{3}{2}a + \frac{1}{2}a^2 \right) \varphi_i + (2a - a^2)\varphi_{i+1} + \left( -\frac{1}{2}a + \frac{1}{2}a^2 \right) \varphi_{i+2} = \varphi(x_i + ah) + O((\Delta x)^3)$$

$$\varphi_c(x_i + a\Delta x) = c_1\varphi_1(x_i + a\Delta x) + c_2\varphi_2(x_i + a\Delta x) = \varphi(x_i + ah) + O((\Delta x)^4)$$

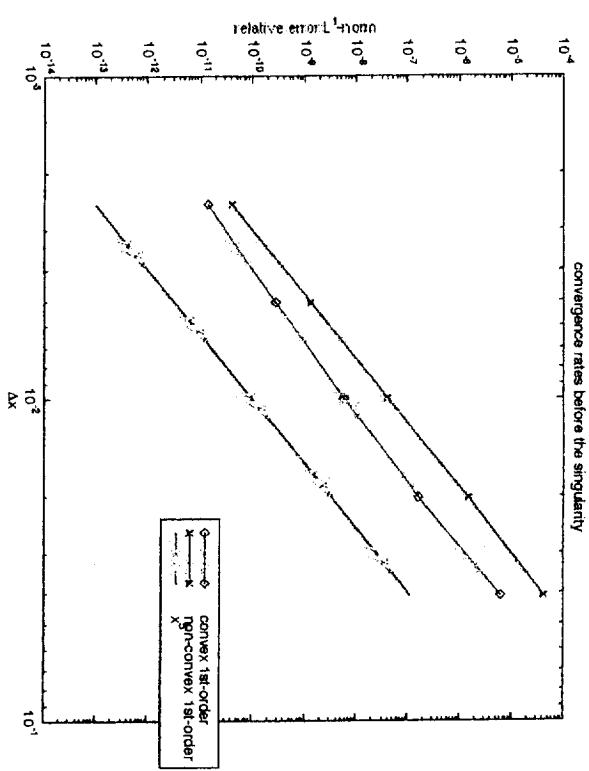
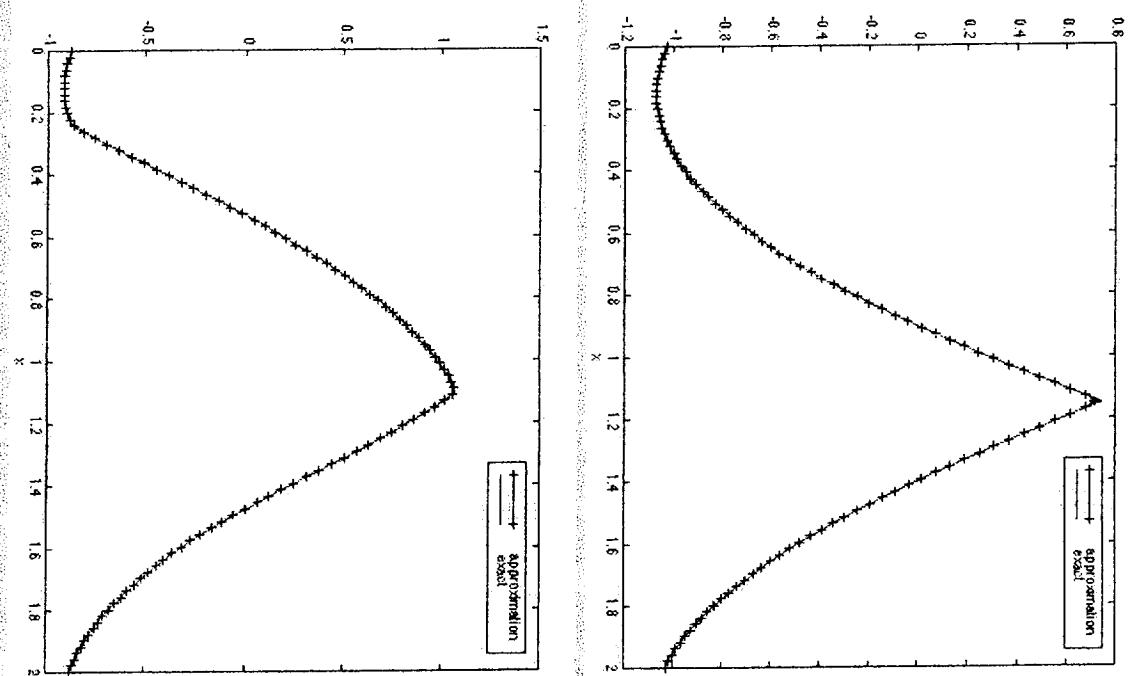
$$c_1 = \frac{1}{3}(2-a), c_2 = \frac{1}{3}(1+a)$$

$$\text{So set } \varphi_w^\pm(x_i \pm a\Delta x) = w_1\varphi_1^\pm(x_i \pm a\Delta x) + w_2\varphi_2^\pm(x_i \pm a\Delta x)$$

where  $w_j = \frac{\alpha_j}{\alpha_1 + \alpha_2}$ ,  $\alpha_j = \frac{c_j}{(\varepsilon + S)^p}$  are defined

to attain high order in smooth regions while suppressing oscillatory interpolants

# 5th-order 1D Results



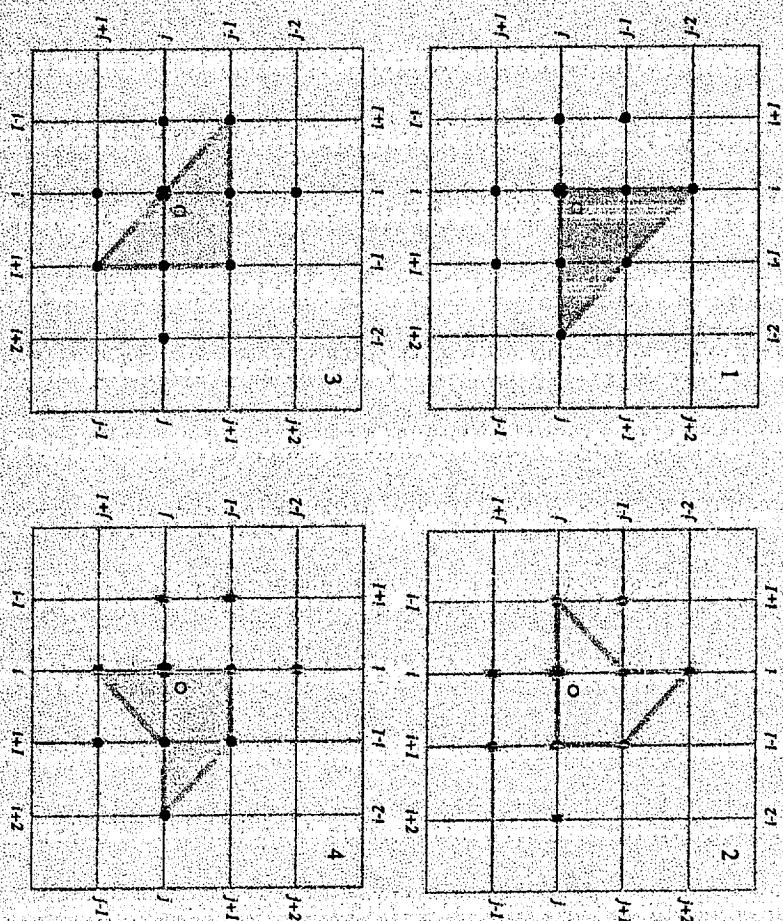
# High-Order 2D Reconstruction

- ★ Three options for reconstruction
- ★ 2D interpolation
- ★ Direction-by-direction
- ★ Interpolate along diagonal
- ★ In all cases, reconstruct derivatives via upwind interpolation



# High-order 2D Stencils

- ★ 3rd-order example
- ★ Stencils enclose evolution point
- ★ Combination covers 10 points required for third order
- ★ Use WENO combination to suppress stencils with oscillations



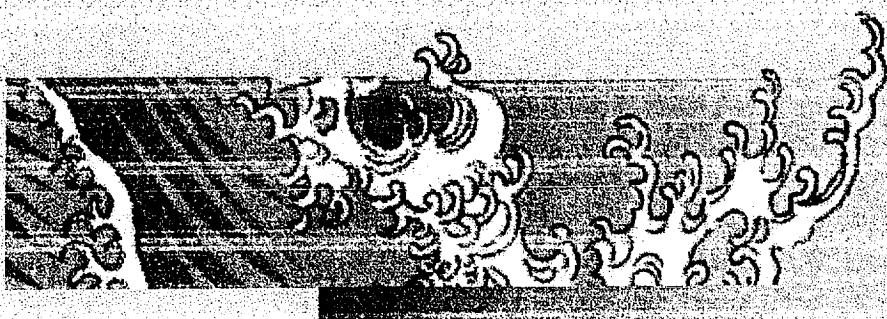
# Direction-by-Direction Strategy

- ★ In 2D:

- ★ 1: interpolate values along coordinate axes
- ★ 2: average coordinate interpolations to evolution point

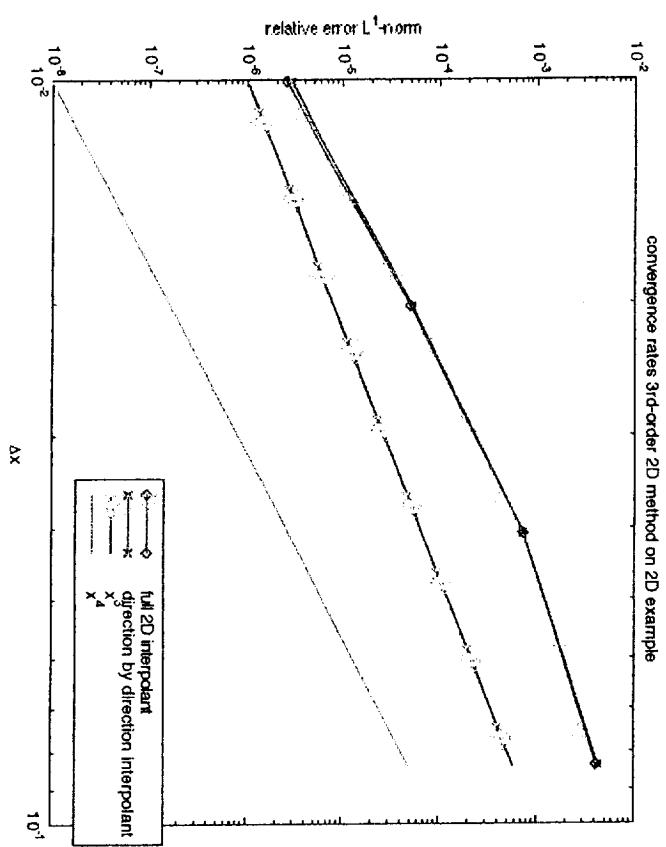
- ★ In  $n$ -D:

- ★ Iterate  $n$  steps, each with  $n$  interpolations



# 3rd-Order Results

- \* Full 2D and direction by direction interpolation have similar quality

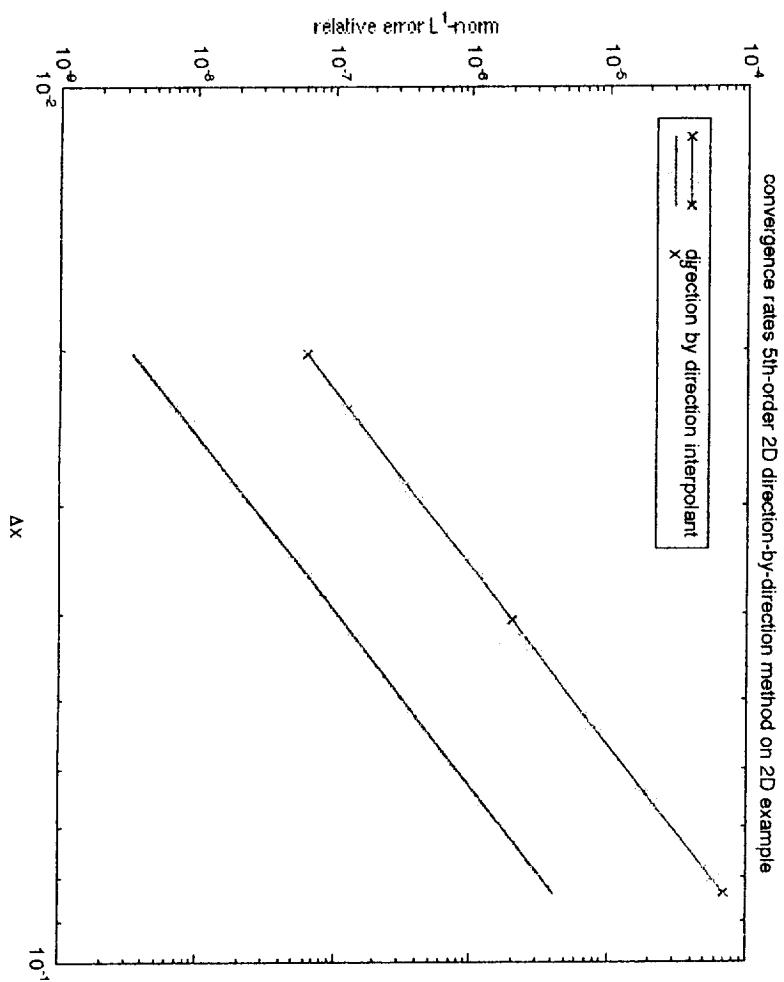


# 5th-order 2D

- ★ Direction-by-direction CWENO reconstruction
- ★ Upwind estimation of derivatives from Jiang and Peng
- ★ Simpson's method for time evolution, using SSP RK4 for mid-values

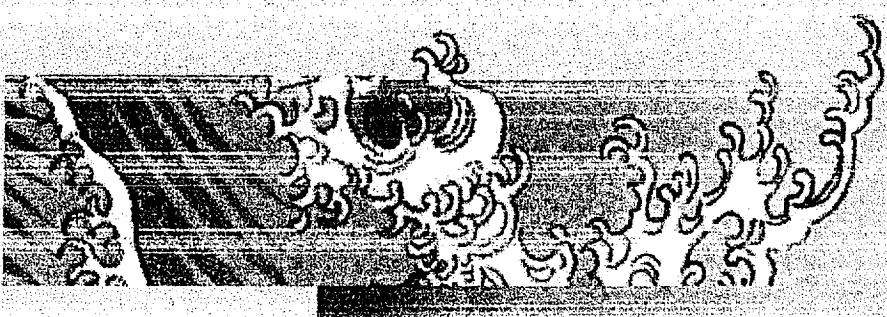


# 5th-order 2D Results



## Scaling to N Dimensions

- ★ Direction by direction will scale better to high dimension than fully dimensional interpolation
- ★ What about upwind? Requires estimation of the maximum of the gradient of  $H$  at each point
- ★ Significant computational burden



# Conclusions

- ★ Developed efficient high-order methods for HJ equations based on central methods
- ★ No need to estimate numerical Fluxes
- ★ Scale well to high dimensions

